The Role of Demand Heterogeneity in Product Innovation Strategy

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Abstract

We investigate the concept of demand heterogeneity in high-tech products through testing for the existence of functionality thresholds, which demarcate the performance level below which a consumer will reject a product-irrespective of price. Above such thresholds, however, the consumer is expected to have no or little marginal utility. If functionality thresholds do exist, then the issue becomes whether new market entrants can capture significant share by offering products at functionality threshold levels with lower prices than existing products - and even perhaps offering additionally new attributes as a differentiation strategy. This study proposes the theory that the "more is better" precept only applies up to the functionality threshold of a product. A key strategic implication of this is that firms targeting the mass market need to adopt more of a modular product strategy to accommodate the heterogeneous demands in functionality requirements. We explore this issue from both a normative and a simulation study, and we discuss the managerial implications of a mass-customization strategy, especially for late entrants in technology product industries.

Key words: demand heterogeneity, technology product, functional threshold, product innovation strategy

I. Introduction

As technology products are now an integral part of most consumer lifestyles, addressing heterogeneity in consumer preferences or/and requirements has become a strategic imperative for technology product firms. Despite the mounting strategic importance, however, the accumulated knowledge on demand heterogeneity in a technology product context remains rather limited to date.

This deficiency, which is found across the majority of innovation and marketing literature, is what our study sets out to address. First, we investigate the concept of demand heterogeneity in high-tech products by testing for the existence of a functionality threshold - a concept introduced recently by Adner and Levinthal (2001). Specifically, a functionality threshold demarcates the performance level below which the consumer will reject a particular product regardless of price. Above this threshold, however, the consumer is expected to have no or little marginal utility. The implication of this is that a substantial number of firms may be offering consumers “performance oversupply” by continuously increasing levels of functionality beyond what is in demand, and thus increasing prices unnecessarily, too. Given that functionality thresholds exist, the main issue is whether new market entrants can capture significant share by offering products at the functionality threshold level and at lower prices than existing products - and even perhaps offering additionally new attributes as a differentiation strategy. Theoretically, the concept that “more is better” should only apply up to the functionality threshold. One key strategic implication that emerges is that firms targeting the mass market need to adopt a more modular product strategy to accommodate the heterogeneous demands of functionality requirements. We explore this issue from both a normative and an empirical standpoint and, in relation to our findings, discuss the managerial implications of a mass-customization strategy.

II. Model Development

There are two issues to consider: functionality threshold and modularity. To shed light on the formation of consumer preference, we began by analyzing consumer choice between an existing product and a new product enhanced with a new attribute. Let us suppose that y_1 is a product with the two attributes a_1, a_2, and y_2 is a tri-attribute product additionally upgraded with a new attribute a_3. We employ the Cobb-Douglas production function for the two products, defined as $y_1 = a_1^{\beta_1} a_2^{\beta_2}$ and $y_2 = a_1^{\beta_1} a_2^{\beta_2} a_3^{\beta_3}$, where $\beta_1, \beta_2, \beta_3$ are the distribution coefficients for the composition of product attributes.

2.1 Consumer Utility

If the product is positioned at an ideal point in an existing market from a consumer's perspective, it is presumed that he or she will optimize the utility which is a function of general consumption x and bi-attribute product y_1 in the bi-attribute product space. The consumer utility maximization problem is obtained by employing the Cobb-Douglas function with the distribution parameters α, β_1, β_2 relatively representing consumers' attribute preferences

$$\text{Max} \qquad U_1 = x^{\alpha} a_1^{\beta_1} a_2^{\beta_2} \tag{1}$$

$$\text{subject to} \qquad I = P_x x + P_{a_1} a_1 + P_{a_2} a_2 \tag{2}$$

where P_x, P_{a_1}, P_{a_2} are the price of general consumption x and the hedonic prices of $a_{1,}$ a_2 satisfying the income constraint, respectively. In the income constraint equation (2), a consumer's purchase cost may be explained by the hedonic function of attributes $a_{1,}$ a_2 related to the product; however, some linear relationship between a_1 and a_2 is assumed without a loss of generality. The Lagrangian function of equation (1) subject to the income constraint (2) is as follows:

$$L = x^{\alpha} a_1^{\beta_1} a_2^{\beta_2} + \lambda(I - P_x x - P_{a_1} a_1 - P_{a_2} a_2) \tag{3}$$

where λ is the Lagrangian multiplier. The first-order conditions of equation (3) are:

$$L_x = \alpha x^{\alpha-1} a_1^{\beta_1} a_2^{\beta_2} - P_x \lambda = 0, \tag{4}$$

$$L_{a_1} = x^{\alpha}\beta_1 a_1^{\beta_1 - 1} a_2^{\beta_2} - P_{a_1}\lambda = 0\,, \tag{5}$$

$$L_{a_2} = x^{\alpha} a_1^{\beta_1}\beta_2 a_2^{\beta_2 - 1} - P_{a_2}\lambda = 0\,, \tag{6}$$

$$L_{\lambda} = I - P_x x - P_{a_1} a_1 - P_{a_2} a_2 = 0\,. \tag{7}$$

By solving the simultaneous equations (4), (5), (6)과 (7), the values of $x, a_{1,}\ a_2$ are

$$x = \frac{\alpha}{\alpha + \beta_1 + \beta_2}\frac{I}{P_x} \tag{8}$$

$$a_1 = \frac{\beta_1}{\alpha + \beta_1 + \beta_2}\frac{I}{P_{a_1}} \tag{9}$$

$$a_2 = \frac{\beta_2}{\alpha + \beta_1 + \beta_2}\frac{I}{P_{a_2}} \tag{10}$$

By inserting the values of equations (8), (9) and (10) into equation (1) of the consumer utility, the consumer's maximized utility in the bi-attribute model is derived as follows

$$V_1 = [\frac{\alpha}{\alpha + \beta_1 + \beta_2}\frac{I}{P_x}]^{\alpha}\ [\frac{\beta_1}{\alpha + \beta_1 + \beta_2}\frac{I}{P_{a_1}}]^{\beta_1}\ [\frac{\beta_2}{\alpha + \beta_1 + \beta_2}\frac{I}{P_{a_2}}]^{\beta_2}\,. \tag{11}$$

In the situation where the bi-attribute product is positioned in the market, if the tri-attribute product $y_2 = a_1^{\beta_1} a_2^{\beta_2} a_3^{\beta_3}$ enters the market, the utility $U_2 = x^{\alpha} a_1^{\beta_1} a_2^{\beta_2} a_3^{\beta_3}$ that a consumer is expected to have is maximized, given the income constraint. A consumer is then supposed to select either the bi- or tri-attribute product. It is important to compare the conditions for consumer choice in the sense that the product, by having a new salient belief added to existing belief, will be positioned in the market either as similar to an existing product or differentiated from it to reflect some innovative change. To model such a comparison, the tri-attribute model is derived on the basis of the bi-attribute model:

$$\text{Max} \qquad U_2 = x^{\alpha} a_1^{\beta_1} a_2^{\beta_2} a_3^{\beta_3} \tag{12}$$

$$\text{Subject to} \quad I = P_x x + P_{a_1} a_1 + P_{a_2} a_2 + P_{a_3} a_3 + C \tag{13}$$

In this model, the switching cost C is introduced as the cost incurred by including a newly developed product in the consumer's consideration set, which is considered as relevant to the consumer's information search for product evaluation (Hauser and Wenerfelt 1990; Roberts and Lattin 1990) and to the firm's advertising level. The Lagrangian function can be obtained in the same way it is with the bi-attribute model, where we can have solution values for attributes a_1, a_2, a_3. By inserting the values into equation (12), the maximized utility V_2 is derived as follows

$$V_2 = [\frac{\alpha}{\alpha + \beta_1 + \beta_2 + \beta_3} \frac{I - C}{P_x}]^{\alpha} [\frac{\beta_1}{\alpha + \beta_1 + \beta_2 + \beta_3} \frac{I - C}{P_{a_1}}]^{\beta_1} [\frac{\beta_2}{\alpha + \beta_1 + \beta_2 + \beta_3} \frac{I - C}{P_{a_2}}]^{\beta_2}$$
$$[\frac{\beta_3}{\alpha + \beta_1 + \beta_2 + \beta_3} \frac{I - C}{P_{a_3}}]^{\beta_3} . \tag{14}$$

2.2 Consumer Choice

If some level of similarity exists among selection alternatives, the estimation of consumer choice probability according to the logit model creates a serious defect as it compromises the IIA property. Thus some means of incorporating similarity among selection alternatives is called for. The GEV (generalized extreme value) model is considered as an appropriate substitute to account for similarity. In the case of the model with two alternatives, consumer choice probability can be represented by estimating a BEV (bivariate extreme-value) model. The BEV distribution with variables Y_1, Y_2 is

$$G(Y) = (Y_1^{1/(1-\sigma)} + Y_2^{1/(1-\sigma)})^{1-\sigma} \tag{15}$$

The probability choice model, consistent with the utility maximization model, is then arrived at. The consumer utility to choose product i is

$$U_i = V_i + \varepsilon_i , \qquad \text{for } i = 1, 2$$

and when ε_i is BEV distributed the equation is

$$\Pr_i = e^{V_i} G_i(e^{V_1}, e^{V_2}) / G(e^{V_1}, e^{V_2}) \tag{16}$$

where G_i represents differentiation of function G with respect to Y_i (i =1, 2). According to equation (16), the consumer choice probability can be expressed as

$$\Pr_1 = \frac{e^{V_1/(1-\sigma)}}{e^{V_1/(1-\sigma)} + e^{V_2/(1-\sigma)}} \tag{17}$$

$$\Pr_2 = \frac{e^{V_2/(1-\sigma)}}{e^{V_1/(1-\sigma)} + e^{V_2/(1-\sigma)}} \tag{18}$$

(McFadden 1978; Maddala 1983), where σ is a coefficient representing a similarity that is approximately the same as ρ, a correlation between products; σ is a value between 0 and 1, where a value of 1 represents identical product correlation and a decrease in value represents a proportional decrease in product correlation. McFadden calculates similarity coefficient, ρ asymptotically, such that $\sigma \le \rho \le \sigma$ +0.045 (Maddala 1983).

III. Simulation Analysis

In this paper we create a meaningful relationship among product characteristics, market characteristics and consumer characteristics; trace changes in the consumer choice probability, given some degree of change in respective characteristics; and attempt to discuss marketing strategies concerning product attributes. We create simulation designs that segment the market based on consumer behavioral factors (income I; switching cost C) and market structural factors (hedonic prices $P_x, P_{a_1}, P_{a_2}, P_{a_3}$), and that position a tri-attribute product in each market segment in a situation where the bi-attribute product has an established presence. To do this, we supposed that consumer taste or the attractiveness of the attributes of the bi- or tri-attribute products can be represented by using the attribute distribution coefficients of $\alpha, \beta_1, \beta_2, \beta_3$, and so on. And we attempt to derive changes in consumer preference formation by allowing for similarity of consumer perceptions of the bi- and tri-attribute products.

For income I, which is one of the consumer behavioral factors, we shall assign 3 different values of 10, 20 and 30 (100$/month), and for switching cost C, incurred in entering into the consideration set, we shall assign 3 different values of 0, 1 and 2. For the market structural factors of the bi- and tri-attribute products, the p_x, p_{a_1} and p_{a_2}, representing the prices of general consumption x, first attribute a_1 and second attribute a_2, were all set to the value of 1, and the hedonic price p_{a_3} of new attribute a_3 was varied between 0.9, 1 and 1.1. Accordingly, in order to understand real world situations, the baseline segmented market is set to a situation where the values of I, C, p_x, p_{a_1}, p_{a_2}, and p_{a_3} are 10, 0, 1, 1, 1, and 1, respectively. By changing the switching cost and hedonic price of the new attribute, we believe that intriguing implications can be delivered that provide insight into real world situations.

In variants of the segmented market, to reflect the product position (a_1, a_2, a_3) and salient belief ($\alpha, \beta_1, \beta_2, \beta_3$) of attributes that consumers perceive, we set both the sum of α, β_1 and β_2 of the bi-attribute product and the sum of α, β_1, β_2 and β_3 of the tri-attribute product to a value of 1. As mentioned, the β_3 stands for interest or salient belief, and its value varies between 0.1, 0.15 and 0.2 in the simulation.[1] In order to reflect a situation where an income budget does not change, the α is fixed at a value of 0.6. Uniform distributions on β_1, β_2 are taken to allow for the heterogeneities of consumers in attributes a_1 and a_2 that can be interpreted as interests or salient beliefs. Simulation designs can be created to calibrate the level of similarity between the bi- and tri-attribute products and to trace probability changes between them according to changes in salient belief related to the new attribute, β_3.

3.1 Strategic Effects of the Late Entrant Product with a New Attribute

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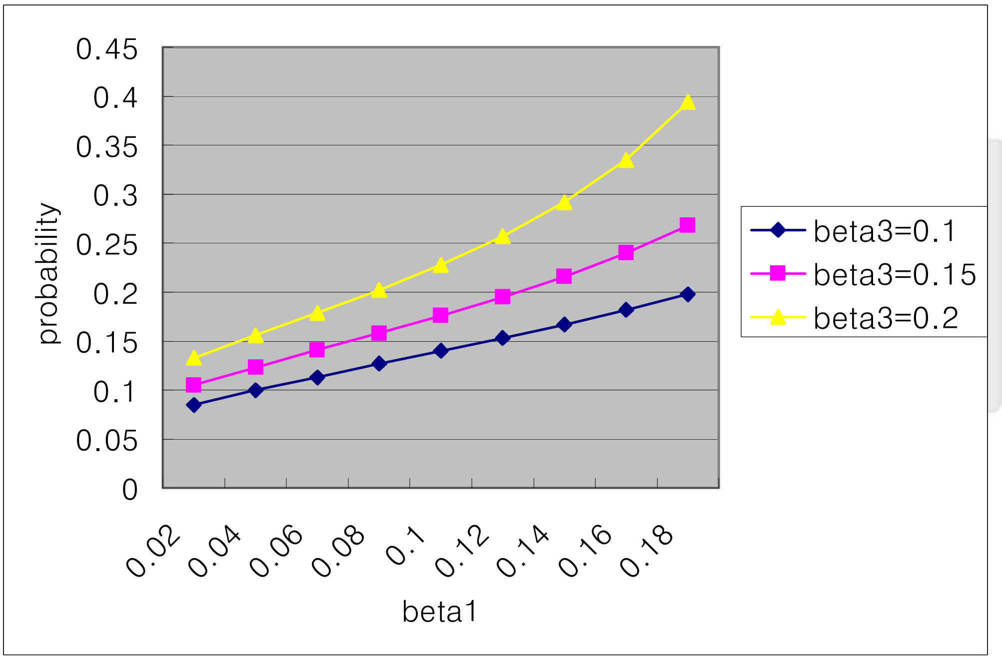
[1] This creates two cases: 1) general consumption decreases; 2) general consumption is constant. In the case where general consumption decreases, α proportionally decreases (e.g., a consumer purchases an upgraded cellular phone instead of purchasing a pair of shoes). In this paper we focus on the general consumption as a constant in keeping with a situation where a consumer budget is constant.

The baseline segment is set to the model where the values of I, C, p_x, p_{a_1}, p_{a_2} and p_{a_3} are 10, 0, 1, 1, 1 and 1, respectively. If β_3, representing taste or salient belief on a new attribute, increases with values of 0.1, 0.15 and 0.2, and, if α is constant at a value of 0.6, the similarity coefficient, σ, will decrease with values of 0.61, 0.504 and 0.419, respectively - as in <Figure 1>. This shows that as similarity between a first and late entrant decreases and that the probability of selecting a late entrant increases.

<Figure 1> Changes in the probability of choosing the late entrant due to increases in the salient belief related to a new attribute : Sigma= 0.61, 0.504, 0.419



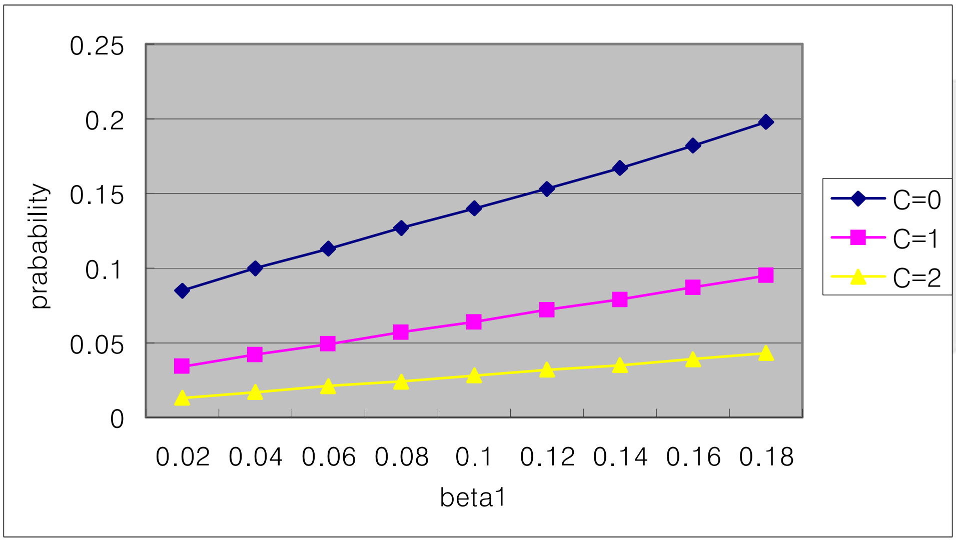
3.2 Effects of the Baseline Late Entrant Product Strategy in Various Segments

If β_3 is held constant at a value of 0.1 and if the switching cost C and hedonic price of a new attribute p_{a_3} are allowed to change, we have the opportunity to investigate effects of the baseline late entrant product strategy in various segments.

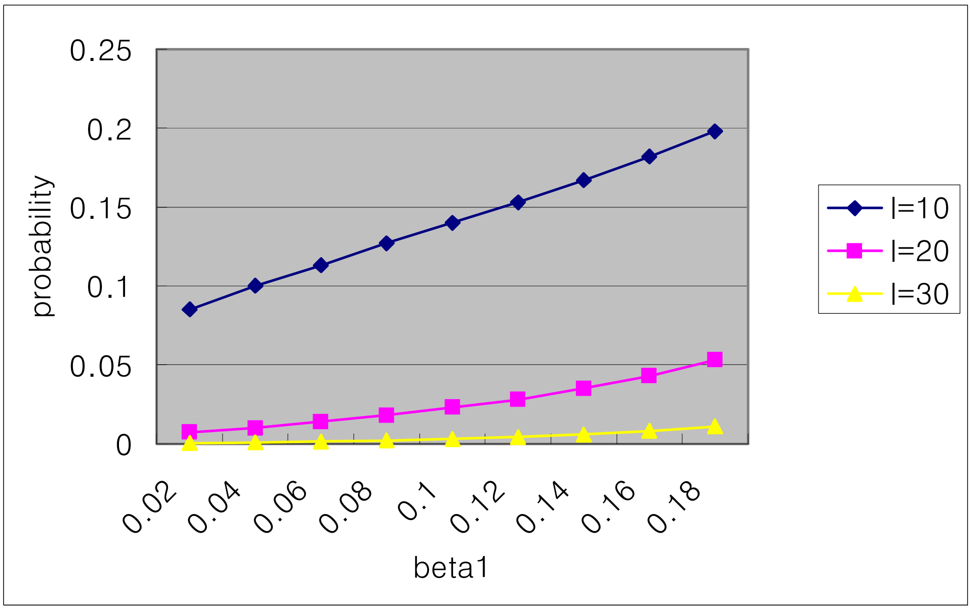
3.2.1 Change in Switching Cost

For switching cost C in segment (I, C, p_x, p_{a_1}, p_{a_2}, p_{a_3}) we shall assign 3 different values of 0, 1, and 2 (100$/month) while the values of the other variables are kept constant in line with the baseline segment. Figure 2 shows that if switching cost increases, a consumer perceives the same level of similarity between the first and late entrant, but has less likely to choose a late entrant.

<Figure 2> Change in the probability of choosing the late entrant with change in switching cost : similarity coefficient = 0.61



<Figure 3> Change in the probability of choosing a late entrant with change in income: similarity coefficients 0.16 (I=10); 0.623 (I=20); 0.634 (I=30).



3.2.2 Change in Income

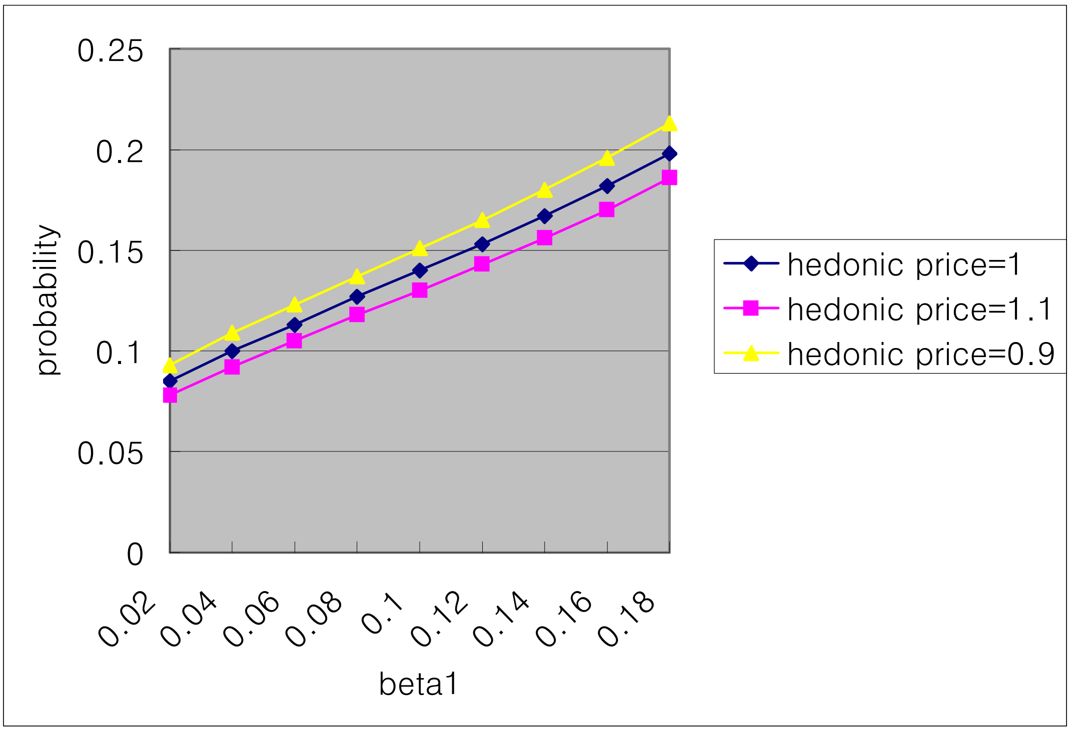
For income I in the segment where (I, C, p_x, p_{a_1}, p_{a_2}, p_{a_3}) = (10, 0, 1, 1, 1, 1), we shall assign 3 different values of 10, 20 and 30. Figure 3 shows that as income I increases, a consumer is less likely to purchase the late entrant. However, this is the result of functional, as shown in equations (11) and (14). It is our understanding that income level affects the probability of choosing the late entrant based on the interaction with a switching cost and, therefore, we must not consider a change in the probability of choosing the late entrant based on a change in income alone. In other words, common sense suggests that a high-income consumer is more educated and has higher opportunity costs than a low-income consumer, which increases the switching; on the other hand, the high-income consumer would be more efficient in searching for information within the same amount of time, which decreases the switching cost. Accordingly, there are coexisting effects that either increase or decrease the switching cost, and so we must develop separate cases to take each conflicting aspect into account.

3.2.3 Change in the Price of a New Attribute

For the hedonic price of the new attribute p_{a_3} in the baseline segment where (I, C,

p_x, p_{a_1}, p_{a_2}, p_{a_3}) equals (10, 0, 1, 1, 1, 1), we shall decrease a value by 0.1 to 0.9 and increase a value by 0.1 to 1.1. Figure 4 shows that, as the price of a new attribute increases, it does not affect a consumer's perception of product similarity, but it does reduce the probability of choosing a late entrant.

<Figure 4> Change in the probability choosing a late entrant given change in the hedonic price of a new attribute: the similarity coefficient is constant at a value of 0.61.



3.3 Propositions on Late Entrant Strategies

Proposition 1: In the segment where the switching cost is less, a consumer's probability of choosing a late entrant will increase.

Generally, a switching cost between non-durables, especially food products such as coffee and ketchup, is low, while the cost between durables, especially high-tech products, is comparatively high (Hauser and Wernerfelt 1990; Urban and Hauser 1989). During the introduction period of the product life cycle, a limited penetration is often detected. As <Figure 2> shows, the market can be segmented with respect to the level of the switching cost and the probability of choosing a late entrant can be derived according to the level of the switching cost.

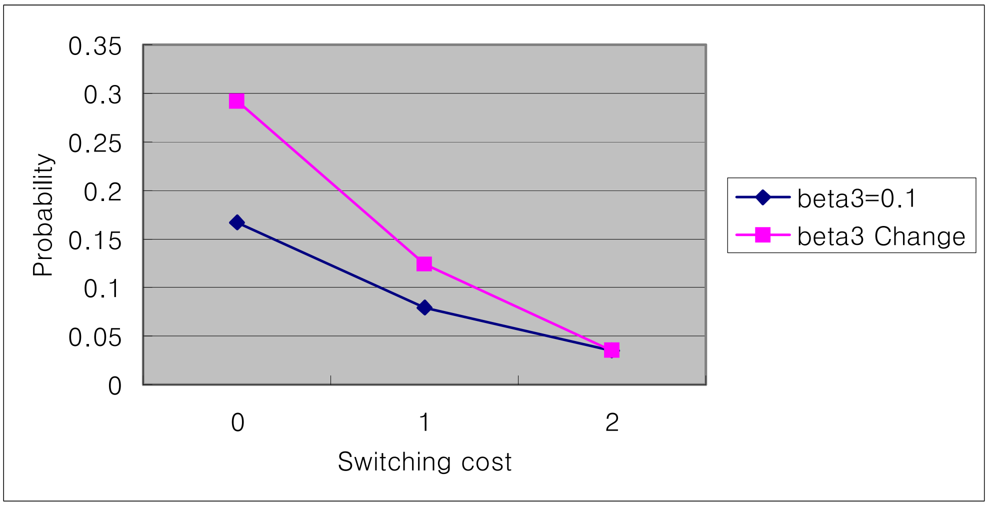
If we take a look at interactions between the income level and switching cost, two effects are found to coexist that decrease and increase the switching cost. Since it is common sense that a high-income consumer is more educated than a low-income one, it follows that they would be more efficient in information searches given the same amount of time, which possibly leads to a decrease in the switching cost. At the same time, since a high-income consumer has higher opportunity in a given time than a low-income consumer, the switching cost is expected to increase. Therefore, we are unable to predict a change in the switching cost given a change in the income level.

Figure 3 shows that in a segment where a consumers' income level is higher, the probability of choosing a late entrant decreases. However, as equations (11) and (14) show, this is a result of their functional forms and, as the income level generally affects a consumer choice through interaction with the switching cost, we believe that it is difficult to detect consumer choice solely on the basis of a change in the level of income.

Proposition 1-1: If a consumer's switching cost for another product is low and their salient belief in a new attribute (β_3) increases, the probability of their choosing a late entrant greatly increases.

Figure 6 shows that, as a consumer's switching cost decreases, there are two resulting cases: 1) salient belief in the new attribute is constant at β_3=0.1; 2) salient belief β_3 increases with values of 0.1, 0.15 and 0.2. That is, if a firm conducts heavy advertising, the cost of a consumer's information search decreases and this can create a market segment with low switching costs. If a consumer's salient belief on the new attribute increases in the low-switching-cost segment more than in the high-switching-cost segment, the probability of their choosing the late entrant increases. This means that a firm would be in the position to pursue a market penetration strategy that adjusts the price level higher as demand for the late entrant increases.

<Figure 6> Change in the probability of choosing the late entrant on decrease of the switching cost and increase of the salient belief on the new attribute



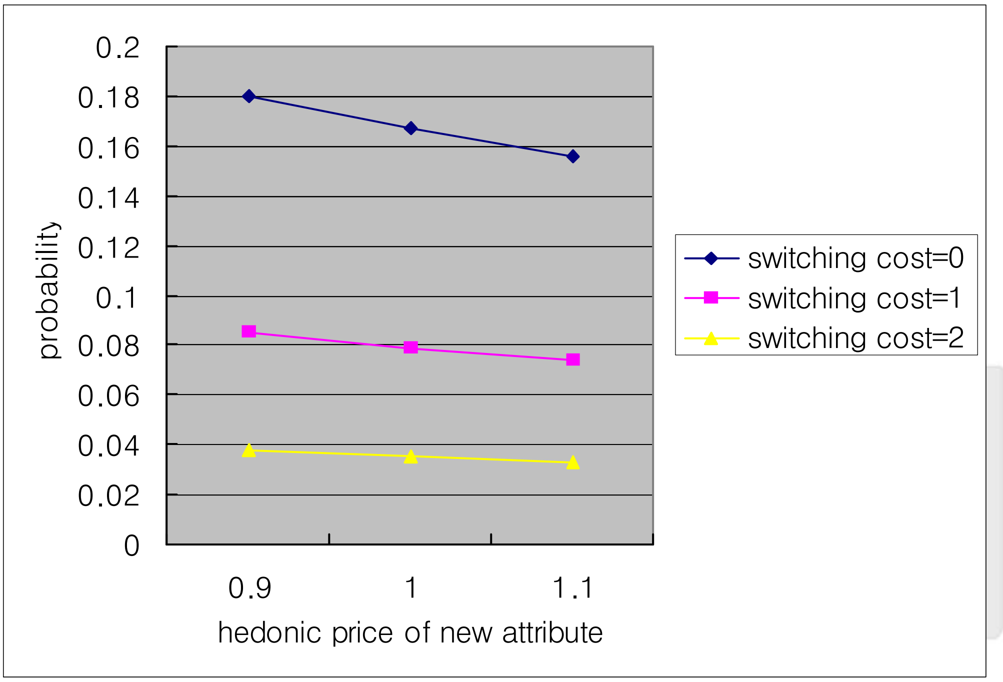
Proposition 2: A consumer's probability of choosing a late entrant would increase in a segmented market with the low rather than a high hedonic price of a new attribute.

Figure 4 shows that, as the hedonic price of a new attribute decreases, the probability of choosing a late entrant increases. Though a hedonic price is determined in the market where the demand outstrips the supply, a firm could have a temporary monopoly position in the case of marketing a product with a new attribute. This can be reflected in the market-deriving strategy to affect the price.

Proposition 2-1: A consumer's probability of choosing the late entrant would rapidly increase in the low-switching-cost segment, where the hedonic price of a new attribute is lower, than in the high-switching-cost segment.

If the hedonic price of a new attribute is low, the firm producing the product can set the price low, so that some innovators will expeditiously adopt the product and most imitators who have yet to do so will learn about it from adopters and not incur a high information search cost. Therefore, the switching cost will become low, which would cause imitators to increase the probability of choosing the late entrant. Figure 7 shows choice behavior of the consumer who is insensitive to the switching cost on a change in the hedonic price of a new attribute, while Figure 8 shows choice behavior of the consumer who is sensitive to the switching cost on a change in the hedonic price of a new attribute, with β_3 constant at a value of 0.1. A consumer's probability of choosing a late entrant is higher in the segment where they sensitively change the switching cost on a change in the hedonic price of a new attribute

<Figure 7> Change in the probability of choosing a late entrant on changes in the hedonic price of a new attribute and in the switching cost

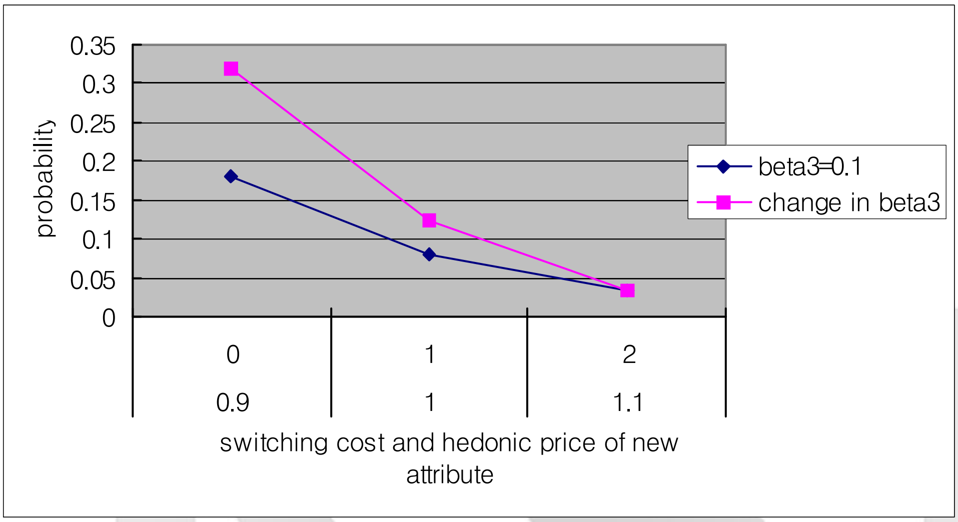


Proposition 2-2: A consumer's probability of choosing a late entrant would increase more rapidly as salient belief on a new attribute is reinforced in the low-switching cost market segment by the hedonic price of a new attribute being lower than in the high-switching cost segment.

In the segment where, as the hedonic price of a new attribute decreases, the switching cost decreases, the probability of a consumer choosing a late entrant increases more rapidly if salient belief on the new attribute increases. That is, for Propositions 2-1 and 2-2, if a late entrant is launched onto the market, a consumer learns about the product by being exposed to advertising and word of mouth. These are, in fact, important themes in new product innovation studies (Bass 1969; Chatterjee and Eliashberg 1989).

Figure 8 shows that, as the hedonic price of a new attribute and the switching cost decrease, there are two scenarios: 1) a consumer's salient belief on the new attribute remains constant; 2) a consumer's salient belief on the new attribute increases.

<Figure 8> Change in the probability of choosing a late entrant on changes in the hedonic price of a new attribute and the switching cost versus change in salient belief of the new attribute



IV. Conclusions and the Future Direction

In this paper we developed a model for consumer preference formation on a late entrant. We set market characteristics with consumer behavioral factors (income and switching cost) and market structural factors (hedonic prices of the attributes employed), and set consumer characteristics with salient beliefs. We performed simulation studies based on market and consumer characteristics, assuming a late entrant product with a new attribute. We also considered the levels of difficulty in learning about and switching to the product according to an innovation level, incorporating into the model a further reflection of salient belief or interest on a new attribute. We attempted to calibrate similarity between a first and late entrant with a new attribute and to design a mechanism to measure changes in consumer choice. All of this is quite different and significant in comparison with Carpenter and Nakamoto (1989; 1994).

If a high level of similarity between first and late entrants is detected in calibrating consumer preference, the general logit model would not be adequate in the sense that its estimation might be biased. The GEV (Generalized Extreme Value) model was employed to reflect the level of similarity into our model.

Apart from the previously mentioned propositions derived from this simulation study, we further propose the marketing of mix strategies from the standpoint of the late entrant.

If a firm adopts a high advertising/high price strategy for a late entrant, switching cost decreases due to the high advertising, which would lead to an increase in the interest on the late entrant and, as a result, the probability of choosing it would increase. However, the transition from innovators to imitators would be restricted by the high price, which would cause a chasm (Moore 1991). Generally speaking, innovative products belong to this scenario. Firms with late-entrant products often use a high-advertising/low-price mix strategy in order to reduce the so-called chasm period and to obtain fast market penetration in spite of the burden of serious expenditure. The justification for this strategy is that, even if the switching cost decreases owing to high advertising, salient belief on the late entrant increases and, simultaneously, the transition from innovators to imitators is expedited sufficiently for the late entrant to rapidly penetrate the market. The low-advertising/low-price strategy can be employed for the launch of similar products onto the market. The strategies proposed above are analogies derived from a consumer preference model. To derive more insightful and meaningful assessments, a profit maximization model needs to be developed from the standpoint of a firm. Nonetheless, this model should be designed on the basis of the consumer preference model proposed in this paper.

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